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Health and the Environment: A Geographical Study of Drugs at Different School Neighbourhoods

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Abstract

This paper studies drug offence at schools and their environment to explain why some but not all schools had drug offences. We used a geographical approach that integrated spatial data of crime, census, and the built environment to identify potential risk factors of drugs at schools. Based on all recorded drug offences at schools (2001-2008) in the region of York in Ontario, Canada, from the police, we geocoded the schools and analysed the associations between drugs at schools and their environment (i.e., neighbourhood characteristics of schools). Neighbourhood characteristics were represented by census socioeconomic variables (including unemployment, lone parent, residential instability, immigration, adults at home, education, and ethnic heterogeneity) and built environment variables (open space and housing type). The analyses were done using geographical information systems for geocoding and extraction of attributes that represent neighbourhood characteristics. Bayesian statistical methods with Markov chain Monte Carlo simulation were used to fit the logistic regression models adopted. One of the major findings was that drug offence at schools and lone parents in the school neighbourhoods is significantly associated. Our findings have the potential to contribute to relevant policy discussions in reducing drug activities at schools. Limitations of the study and further research are discussed.

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1. Introduction

The Canadian Addiction Survey (CAS) reported that 44.5% of Canadians used cannabis at least once

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in their lifetime. Identifying that the peak rate of use was among 18 and 19-year-olds, it recommended further investigation with the use of cannabis by youth. For other illicit drugs, approximately one in six Canadians had used them in his or her lifetime [1]. Bill C-15 act is an initiative of the Canadian federal government's national anti-drug strategy that aims to institute minimum sentences for serious drug offenders. Is throwing drug offenders into prison a solution to drug use? While we think of increasing penalty to offenders, perhaps we should try to understand more who these drug offenders are. What are their social and family backgrounds? What sort of neighbourhoods do these offenders live or study? Can we target neighbourhoods or schools instead of individual offenders to reduce the problem of drug use by implementing appropriate social policies to specific neighbourhoods or schools that are of concern? Our research aims to address these questions through identifying the characteristics of the neighbourhoods of the schools with drug offence.

Drug use or prevention at school has been studied [2] but less often using a geographical approach that utilizes variables of both census and the built environment. Also, in most small-area studies of crime, incidences of offence or offenders were accumulated in years and used to represent outcomes in regression analyses, not so often were incidences analysed separately year by year. This research integrated spatial data of crime (drug offence at schools), socioeconomic characteristics of the neighbourhoods of schools (such as ethnic heterogeneity and lone parents from the census survey) and the built environment (housing type, open spaces) to identify potential risk factors of drug offence at schools using a Bayesian approach. The Bayesian framework models incidence of offences year by year as repeated measurements [3].

2. Study Area and Period

Our study area is in the region of York in Ontario, Canada. The census division of York consists of nine municipalities. We studied all the 273 schools in the region. The study period is from August 31, 2005 to August 30, 2008 (three years).

Fig. 1. Map of all the 273 schools in the region of York, Ontario. Triangular and circular dots represent schools with and without drug offence, respectively, between August 31, 2005 and August 31, 2008. The boundary lines demarcate the census disseminate areas (smallest census areal units that cover all parts of Canada) in the region.

3. Data

The region of York police provided data of recorded offences in all of the school in the region between August 31, 2005 and August 31, 2008. During this period, there were 3,232 school offences and 9% of which (i.e., 293 cases) were drug offences. These drug offences were given URC (Uniform Crime Reporting) violation codes of 4140, 4220, 4230, or 4240, which include possess cannabis, trafficking or intent to traffic cocaine or cannabis. Of all the 273 schools in the study region, 64 schools (23%) have recorded crime of drugs.

Identification of risk factors of drug offence at schools follows the theory of social disorganization [4, 5] and Wilkstrom model that explain offence locations [6]. Socioeconomic variables including unemployment, lone parent, residential instability, and index of ethnic heterogeneity; and built environment variables including land use, specifically open space areas, and housing type (percentage of apartment) were used to represent the characteristics of the neighbourhoods of the schools. The index of ethnic heterogeneity varies between 0 and 1 where 0 implies ethnic homogeneity and the index approaches 1 as ethnic diversity increases [7]. Open space areas contain 24 types of open ground, which include campground, cemetery, national parks, sports field, picnic site, sports track, botanic garden and exhibition ground.

Census 2006 is our source of socioeconomic data. Our study region consists of 1,133 census dissemination areas (DAs). DAs have an average population of 400 to 700 persons. It is the smallest census area unit that covers all parts of Canada. For each school, socioeconomic attributes of the DA that the school falls within were used to represent the characteristics of the school. For land use, schools were classified according to the presence or absence of open space area at the proximity of the school. Of the 273 schools, 61 schools have open space areas within 500 metres.

4. Methodology

The analyses were done using geographical information systems for geocoding and extraction of social and environmental variables that represent the neighbourhoods of the schools. Bayesian statistical methods with Markov chain Monte Carlo simulation were used to fit the logistic regression models.

4.1 Geocoding of schools with drug offence

We geocoded all schools in the study region using ArcGIS based on the addresses of the schools and a street network file of the region. Each school could then be represented geographically by a point on a map. Point-in-polygon search enables the identification of DA within which the school falls within and thus the neighbourhood characteristics (covariates) of the school. The geographical points also provide information about the proximity of each school to open spaces.

4.2 Modeling Strategies

Let Y(i) denotes the binary response variable referring to the ith school. Y(i) = 1 if the ith school has drug offence within the study period and Y(i) = 0 otherwise. Then,

$$Y(i) \sim \text{Bernoulli}(p(i)), \qquad (1)$$

where ~ denotes “is distributed”

$$\text{logit}[p(i)] = \log[p(i)/(1-p(i))] = \beta_0 + \beta 1X1(i) + ... + \beta kXk(i), \quad i = 1,...,n \qquad (2)$$

where p(i) is the probability that the ith school has drug offence, X1,...,Xk is the set of covariates (potential risk factors) and $\beta_1,...,\beta_k$ the corresponding regression parameters. Note that there are as many {p(i)} as there are schools in the study area (i.e. n, here n=273). The parameters of interest are {βj} since there are only k of these (k<n) and inference on these parameters determines the statistical significance of the corresponding covariates in the model.

4.3 Implementation

Equations (1) and (2) were fitted using WinBUGS (http://www.mrc-bsu.cam.ac.uk/bugs/), which is a freeware for fitting Bayesian models. Detail of similar model fitting in crime analysis has been published [8]. In the absence of genuine prior expectations about the direction and size of covariate effects, we used a non informative priors for all the regression coefficients, which is a normal distribution with mean zero and large variance (variance=10,000). Two chains were run. Convergence was monitored by visual examination of the trace plots of the samples for each chain and autocorrelation graphs. Convergence was quick for the models fitted and occurred by 1,000 iterations. These samples were discarded as "burn-in". An additional 5,000 samples were used to generate the posterior distributions from which estimates of the parameters were obtained by computing posterior means using Monte Carlo integration.

5. Result of Analysis

Nine covariates that represent the environment of the school were fitted to the multivariate logistic regression model, i.e., equation (2): percentage of apartments, index of ethnic heterogeneity, rate of immigration, percentage of adults at home, percentage of high education, residential instability, unemployment rate, percentage of lone parents, and with or without parks within 500 metres of the school.

To account for socioeconomic characteristics in areas of proximity to the school, we run the analysis using the average of socioeconomic values within 500 metres of the schools, i.e., at the school neighbourhood level (see Figure 2). For example, if a school has five DAs within its 500 metres buffer, then the percentage of lone parents assigned to that school equals the average percentage of lone parents of the five DAs. Other buffers such as 1,000 and 2,000 metres were tried but not adopted due to enormous overlaps of buffered polygons giving rise to similar attribute values among schools.

Percentage of lone parents is the only covariate that is associated with drug offence at schools at the 5% significance level after controlling for the type of school (primary or secondary). The association is positive, which makes sense. A map of the counts of drug offences at schools and percentage of lone parents also suggests their positive association (see figure 3). Areas that have low percentage of lone parent tend to have low count of drug offences at schools.

Fig. 2. Map showing the 500-metres buffer from each school and the DAs in the study region. Data of the DAs that fall partly or wholly within the buffer of a school were used to describe the neighbourhood characteristics of the school.

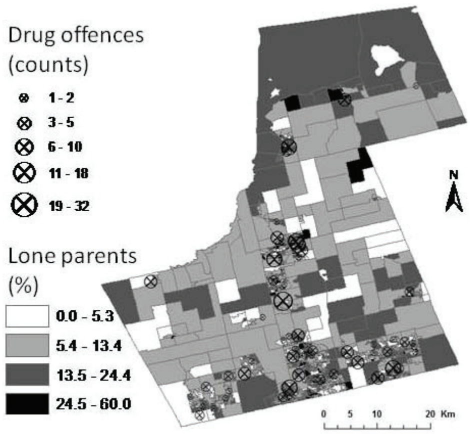

Fig. 3. Map showing counts of drug offences for the 273 schools and percentage of lone parents at the census dissemination area level in the region of York, Ontario.

6. Discussion

There are limitations in this study in terms of methodology and data. Explanatory variables (such as unemployment rate and percentage of apartments) used in the analysis of crime are often correlated. The variables that were used would tend to correlate with other socioeconomic variables not included in the model that do affect drug offence at schools. The fact that some or all explanatory variables are correlated does not, in general, affect inferences provided that the inferences are made within the region of observations [9]. When multicollinearity exists, the estimated regression coefficients individually might become statistically insignificant even though a definite statistical relation exists. Our result indicates that lone parent is significantly associated with whether a school had drug offences. False negative of association might exist with other explanatory variable in the model due to multicollinearity.

Another limitation of our study is our inability to distinguish between schools of different categories (e.g., public vs. private schools, primary vs. secondary schools) and schools with high vs. low counts of drug offences. In modeling outcomes, we expect to obtain more consistent results if drug counts (modeling as binomial distribution) instead of presence or not (modeling as Bernoulli distribution) were analysed. However, we were not able to access data that represent appropriately the population at risk at each school to fit a binomial (instead of a Bernoulli) model.

7. Conclusions

Further research that includes offender data in the analysis should enable us to learn more about drug offences at schools. If our finding that schools with neighbourhoods that have higher percentage of lone parents have more drug offences is valid, then it suggests that it is possible to reduce a school's drug activities by changing its neighbourhood characteristics. Drug dealers living near schools, who have lone parents, might have drawn students nearby to drug activities. They might also be students in the schools. And, if we assume that most students at a school live at the neighbourhoods of the school, which is a reasonable assumption, then our result indicates that students with lone parents were more vulnerable to commit drug offence, probably because they lack good parental care. In this regard, intervention to educate the public regarding the problem of drug misuse should target neighbourhoods with high rate of lone parents. However, we would need to analyse data of (drugs at school) offenders' residences to investigate if such intervention is appropriate. Does the neighbourhood/environment of the school or/and offender's residence matter for drug offence at school? Further research that analyses offender data would help to learn more about drug offence at schools. Personal characteristics of offenders, such as lone parents, are usually not recorded by the police, but offenders' addresses are usually recorded. Geocoding will enable the identification of neighbourhood characteristics of offenders' residences based on census information. This will provide a good estimate of offenders' family and other socioeconomic backgrounds provided that the smallest census area unit (such as DA), where within variation of characteristics is minimal, is used as the unit of analysis. Furthermore, future research can included the use of census macro data, with which Bayesian modeling can take into account heterogeneity of socioeconomic characteristics within the unit of analysis (DA for instance) to reduce ecological bias [10].

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